Synopsis for Registration as Research Student

For

Doctoral Degree

On

“Crop Disease Detection Techniques”

By

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Abstract

Accurate diagnosis of plant diseases is a complex challenge faced by farmers during the growth and production stages of the plant. In the case of plants, the disease is defined as any impairment of the normal physiological function of plants that produces characteristic symptoms. A symptom is a phenomenon associated with a thing and considered evidence of its existence. A disease is caused by a pathogen, i.e., an agent that causes a disease. In most cases, pests or diseases are identified on the leaves or stems of plants. Therefore, the identification of plants, leaves, and stems, as well as the detection of pests or diseases, the percentage of occurrence of pests or diseases, and the symptoms of pest or disease infestation play a key role in the successful cultivation of crops. Diseases are found to cause severe crop losses, amounting to financial losses. In order to address this problem an improved deep-learning model for accurately diagnosing diseases of plant leaves. First, to diagnose diseases, use the algorithm to cluster sample images and then feed them into the improved deep learning model.

1. Introduction

Conventional agriculture relies on the use of a high level of chemical inputs such as fertilisers and pesticides. These inputs imply environmental hazards and health risks. There is an increasing concern among citizens and consumers about the attested presence of pesticide residues in the environment and food. Recent European and French incentive policies clearly targeted a reduction in pesticide use in all agricultural systems as a key option to reduce the contamination of the environment. Such a decrease in pesticide use is crucial for the implementation of sustainable agricultural systems. The challenge is especially high in crops where pesticides are recurrently applied to control numerous pests and diseases [13]. Artificial extinction also changes shoot demography by increasing the proportion of long shoots. CT is therefore likely to modify canopy aeration, and alter vegetative growth dynamics and rhythmicity, potentially affecting the development of some foliar pests or pathogens [14].

There is a challenge in satisfying a societal demand for environmentally friendly systems and healthy crop, and keeping pests and diseases below economic thresholds to maintain the growers' income in an evolving regulation context. The preservation and promotion of biodiversity within agricultural landscapes could be a key issue to answer both ecological and agronomic purposes [15]. There are a number of problems in increasing the world's population, increasing the volume of crop products and providing them with quality crop products, increasing productivity, reducing the damage caused by diseases. The loss of an average of 20-40% of cultivated crop products under the influence of diseases requires the improvement of the system of control of these diseases. It is necessary to use modern information technologies in the fight against diseases, to collect relevant information quickly and as required, to automate the process of collecting, processing this information and making optimal decisions based on them and delivering them to the consumers. The development of information systems for the collection, storage and processing of information is of great scientific and practical importance in determining the data affecting the development and spread of diseases [16].

There is limited data regarding the specific problems faced by organic crop growers when dealing with plant protection, though some general knowledge about disease incidence can be found. Such information is crucial to improve the efficacy of a targeted knowledge transfer to organic crop growers and advisors aiming at an increased adoption of innovative practices. Even though a general knowledge about disease incidence in crops can be found, there is limited data regarding the specific problems faced by organic crop growers in this respect,

particularly on a wider territorial level as it could be that of the nation. This information, however, could be crucial in order to improve the efficacy of knowledge transfer to serve the organic crop sector and increase adoption of innovative practices [17]. Federated learning (FL) is an emerging distributed learning technique, which can effectively solve data silos and privacy issues. FL can train models on local data on decentralized devices and then aggregate these local models to achieve updated models. This collaborative model training approach for decentralized data allows each server to maintain control of local data while obtaining a shared model that integrates the advantages of each party's data [18], [19]. FL not only reduces the communication cost and relieves the pressure on data storage and data processing of cloud servers but also improves the model training efficiency and model generalization capability. However, due to the heterogeneous devices of FL participants, coupled with the unreliable wireless link connection between participants, there is still a high communication cost despite avoiding the uploading of large amount of data [1].

2. Motivation

Plant disease research requires the study of visually detectable patterns on the plant. Plant health monitoring and disease detection are critical to long-term agriculture. Manual monitoring of plant diseases is quite difficult. It requires a lot of effort, knowledge of plant diseases, and an unreasonably long processing time. The development of an automated system will help farmers detect and identify plant diseases, reduce human errors, improve segmentation accuracy and shorten segmentation time.

This automated system will assist farmers in the early detection and treatment of plant diseases. Plant disease transmission can be significantly slowed through early detection and prevention. At the same time, fewer drugs or pesticides can be used to prevent or control plant diseases before they reach a critical stage, resulting in less environmental impact and lower costs for farmers. Consequently, this technology for autonomous detection of plant diseases will be a scourge for society and have a significant impact on agriculture.

3. Literature review

There are so many techniques out of eight existing techniques of disease and pest detection using federated learning that are discussed below along with their merits and demerits as shown in Table 1.

Table 1: A literature survey

Authors	Methods	Advantages	Disadvantages	Data Set
Deng, F *et al.* [1]	Federated learning (FL) and improved faster region convolutional neural network (R-CNN)	Beneficial to shorten the detection time and enhanced detection accuracy.	Did not able to improve the convergence speed of the model.	In order to train an excellent detection model, 15,522 image data obtained by the sample expansion method are divided into the training set, verification set, and test set according to the ratio of 3:1:1.

Jianjun Ni, et al. [2]	Improved faster region with convolutional neural network features (RCNN) network is used to extract the features of representative objects in the scene to obtain local features.	An improved Inception module is used to extract global features, where a mixed Leaky ReLU and ELU function is presented, to reduce the possible redundancy of the convolution kernel and enhance the robustness.	However, there are some limitations of the proposed method, including the division problem of the scene categories and the classification problem for some heterogeneous scenes, such as the roadside parking lots and gas stations along the street. These problems should be further studied.	There are five categories of the scene in the proposed dataset, namely, crosswalk, gas station, parking lot, highway, and street. Each category has 15 000 pictures that are selected from the public datasets KITTI, Place365 and BDD100k.
Yu He, et al. [3]	Proposed Multilevel-feature fusion network (MFN)	The system is a DL network that can obtain the specific category and detailed location of a defect by fusing the multilevel features.	The data augmentation technology is due to the expensive manual annotations in detection datasets. The defect segmentation task with DL technologies can obtain a more precise defect boundary.	The training set contains 1260 images used for fine-tuning the network introduced in section IV-B, and the test set contains 540 images.

Wenqing Zhao, et al. [4]	Improved Faster RCNN algorithm for insulator recognition and fault detection, which is a combination of Faster RCNN and improved FPN.	The fault detection results are more accurate in comparison. The algorithm is applicable for both bunch-drop and crack fault detection.	improving the computing speed of the algorithm and applying it to practical engineering.	3234 glass insulator images including 2000 composite insulator images.
Xiaohan Yu, et al. [5]	The author proposes an asymmetry tolerant part segmentation network (ATPNet) an asymmetric tolerant part segmentation framework for visual tasks.	The proposed asymmetry loss serves as a constraint to spatially align self-similar parts based on how symmetric they are to each other, thus leading to a more semantically meaningful part segmentation.	The main limitation is that, even with the proposed constraints, weakly supervised segmentation may not function perfectly especially on objects with cluttered background or severe overlap of different parts.	The proposed ATP-Net has achieved superior/ competitive performance on 12 datasets.
Türkoğlu, M. and Hanbay, D [6]	Deep learning-based features	Provided lower training times and had higher accuracy scores.	Did not use regional images and improved CNN models for attaining enhanced classification performance.	The dataset includes a total of 1965 images belonging to eight different plant diseases

Turkoglu, M *et al.*[7]	Pre-trained convolutional neural networks	Found to be more successful under different datasets.	Did not use feature reduction methods to select the best features.	A dataset consisting of 15 classes and 4,447 unconstrained disease and pest images is collected
Khan, F.S *et al.*[8]	EfficientNet B03 method	Very less computation power during the classification of pests for the agricultural environment.	Classification of pests in real-time is a difficult process.	The augmentation stage produced 600 images for each class, total 5400 images for pest detection.

3.1 Performance Parameters Relative Use for Research

- **Lossy Function:** It's a method of evaluating how well your algorithm models your dataset.
- **Mean Square Error:** Mean or Average of the square of the difference between actual and estimated values.
- **Root Mean Square Error:** It's a measure for evaluating the quality of predictions.
- **Mean Average Precision:** It calculates the weighted average of precision at each threshold.
- **Precision:** It's measuring the accuracy of positive predictions, (Precision = True Positive/True Positive + False Positive)
- **Recall:** It measures the completeness of positive predictions. (Recall = True Positive/True Positive + False Negative)
- **F-measure:** The F1 score is the harmonic mean of both precision and recall.
- **Throughput:** It is a measurement in Machine Learning to determine the performance of various models for a specific application.
- **Accuracy:** It is one metric for evaluating classification models.

3.2 Identified Open Research Problem

Fangming Deng, et al. [1] show that mean average precision (mAP) is 89.34 % using federated learning (FL). There is scope to increase mAP by modifying key point extraction strategies for training method.

1) There is limited work observed on crop disease detection.
2) There is not enough research on the detection of dense targets.
3) There is a scope for improving the accuracy and convergence speed.

4. Methodology

The primary intention is to design and develop a technique for multiple diseases and pests detection in federated learning. Here, the entities involved for the processing includes nodes and server. The process involved are as follows: Here, the local training will be done based on local data at every node, and then updating to server will be done followed by model aggregation at server. Finally, the global model at nodes will be downloaded, and training will be updated based on downloaded global model and the local model and this process will be iterative at every epoch. Figure 1 shows the Block Diagram of Training Model Using Deep Learning. In the training model phase, the input images will be collected. Thereafter, the pre-processing will be done using mean filtering. Then, the segmentation of input image will be done using PSI NET [12]. The image augmentation will be done using position augmentation that includes various transformations like Padding, Rotation, and Translation. The Feature Extraction will be done to extract Histogram of Gradients (HoG), Local Binary Patterns (LBP), and a set of statistical features. The multiple disease detection will be done using proposed hybrid Shuffle-SpineNet. The Shuffle-SpineNet will be provided by unifying the ShuffleNet [10] and SpinalNet [11]. Finally, the pest's detection will be done using hybrid Shuffle-SpineNet. The objective model considered are Resource Required, Local Timing Delay, Global Timing Delay, Local and Global Loss Function. Moreover, the Local updation and aggregation at server will be modified based on the Average method. Moreover, the implementation of the proposed method will be carried out in a PYTHON tool using New Plant Diseases Dataset [9] and image dataset taken from field. In addition, the proposed method will be analysed using different performance metrics, such as Resource usage, Loss Function, Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Average Precision (mAP), Precision, Recall, and F-measure. The performance of the developed method will be implemented, and it will be compared with existing methods to reveal the effectiveness of the proposed method. Figure 2 shows the Block Diagram of Deep Learning Based Crop Diseases Detection Technique.

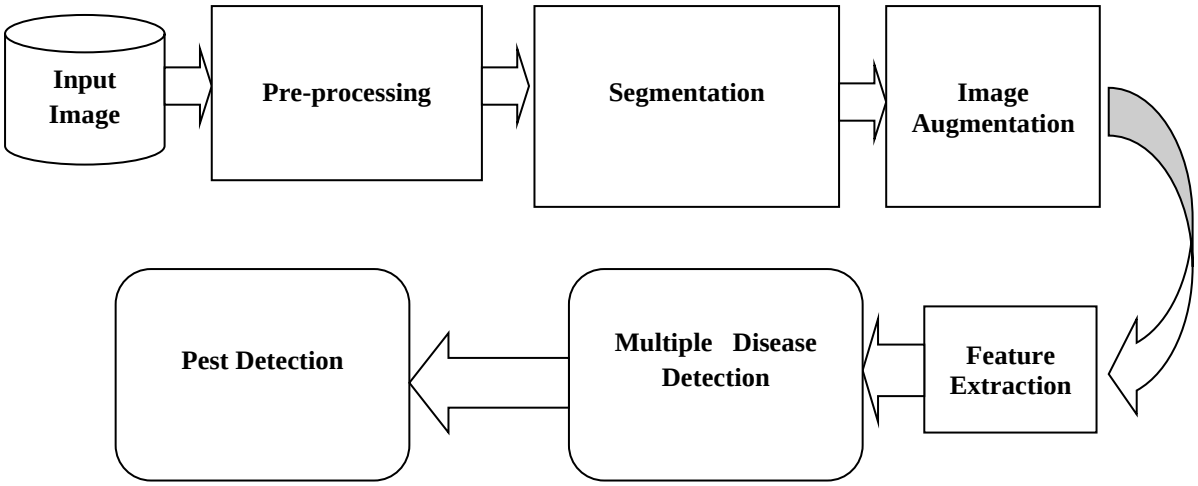

Figure 1. Block Diagram of Training Model Using Deep Learning.

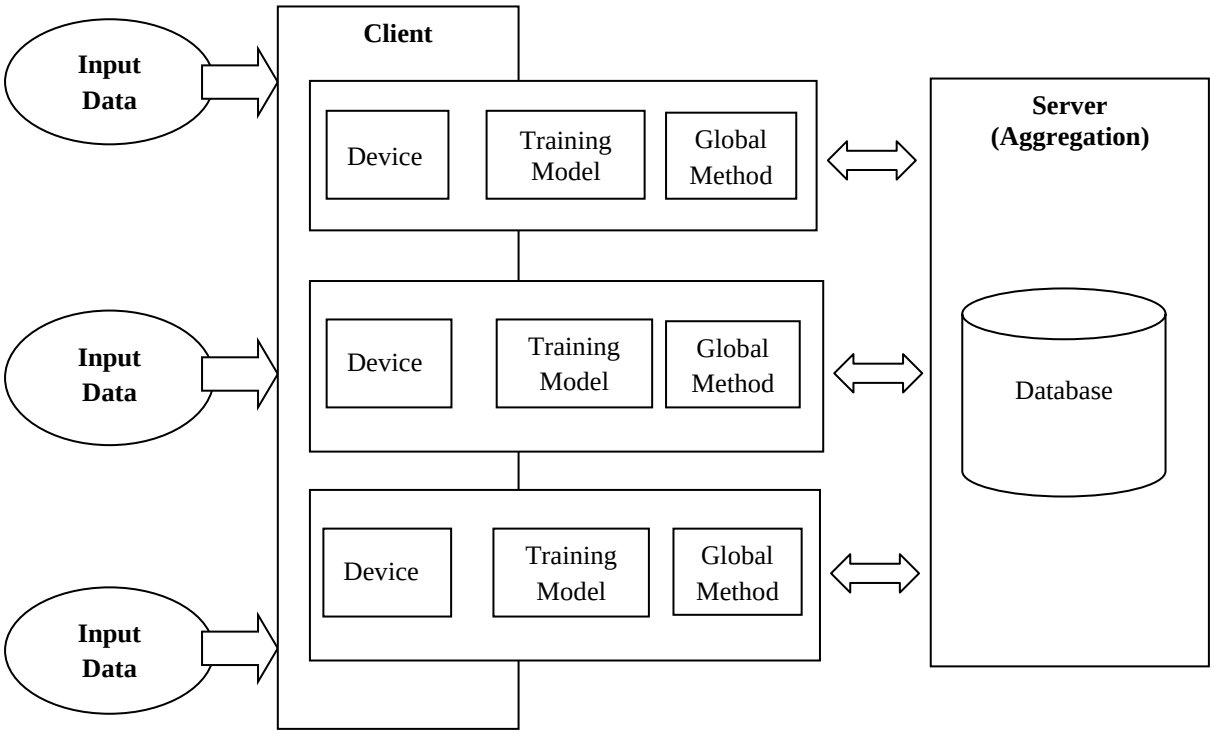

Figure 2. Block Diagram of Deep Learning Based Crop Diseases Detection Technique.

5. Problem Definition

Nowadays crops like soybean, potato, corn etc. face many traits/diseases and insect damage is one of the major ones. Insecticides are not as efficient as we hope. Moreover, there are environmental issues as insecticides may be toxic to some kind of birds, and damage natural animal food chains. A common practice for plant scientists is to estimate the diseased leaf damage by eye on a scale based on a percentage of the affected leaf. The damage is estimated without photo documentation.

In this research, it is proposed to undertake a detailed investigation of customized deep learning algorithms for processing plant leaf/stem images mainly in color to identify traits/diseases to improve both accuracy and throughput.

6. Future Research Plan - Aims and Objectives

The foremost purpose of the research work is to propose the best techniques in Disease and Pests Detection with classification.

Objectives:

The objectives are listed below.

- To make a review and analysis of existing methods for disease detection.
- To propose a segmentation model to extract appropriate features to improve the segmentation performance.
- To design and introduce an algorithm for classifying the type of disease.
- To analyse the performance of the developed algorithm.

7. Conclusion

It is expected that new a system will be presented for the identification of diseases in plant leaves or stems. The proposed work will introduce methods that will automatically extract contents to form a feature vector for each image. The deep learning system will be used to categorise and identify diseases, and results will store in a database.

8. Proposed Work Plan

Figure 3 shows the proposed work plan for research work.

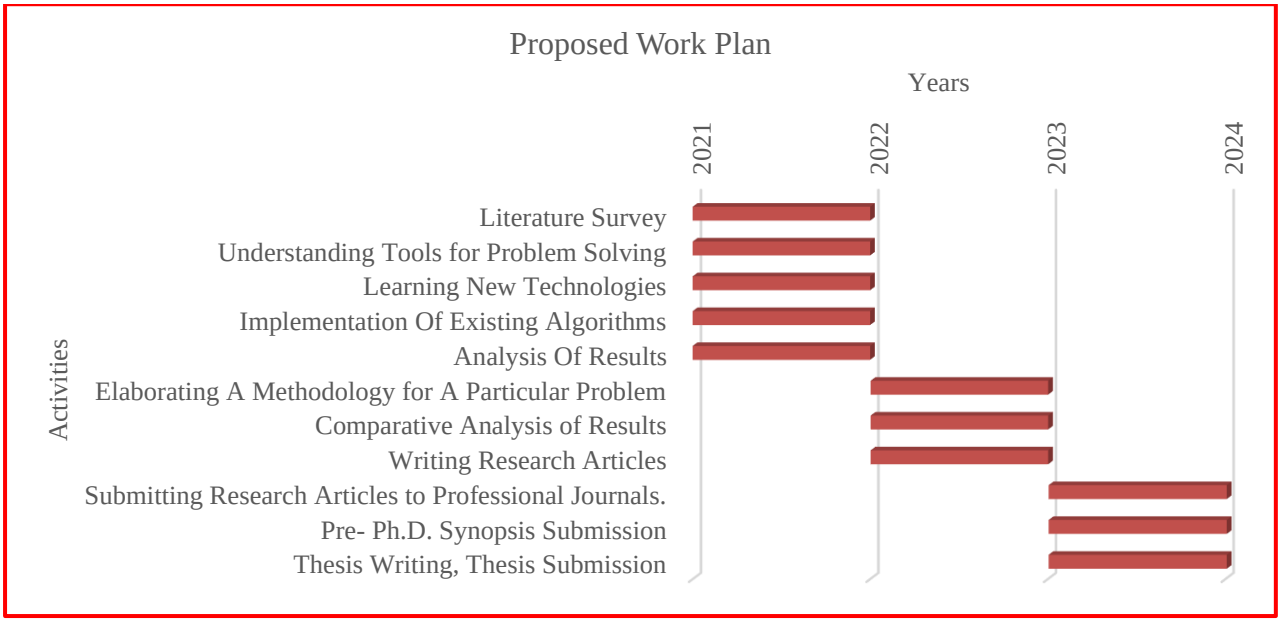

Figure 3. Gantt Chart of Proposed Work Plan

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